

## Introduction

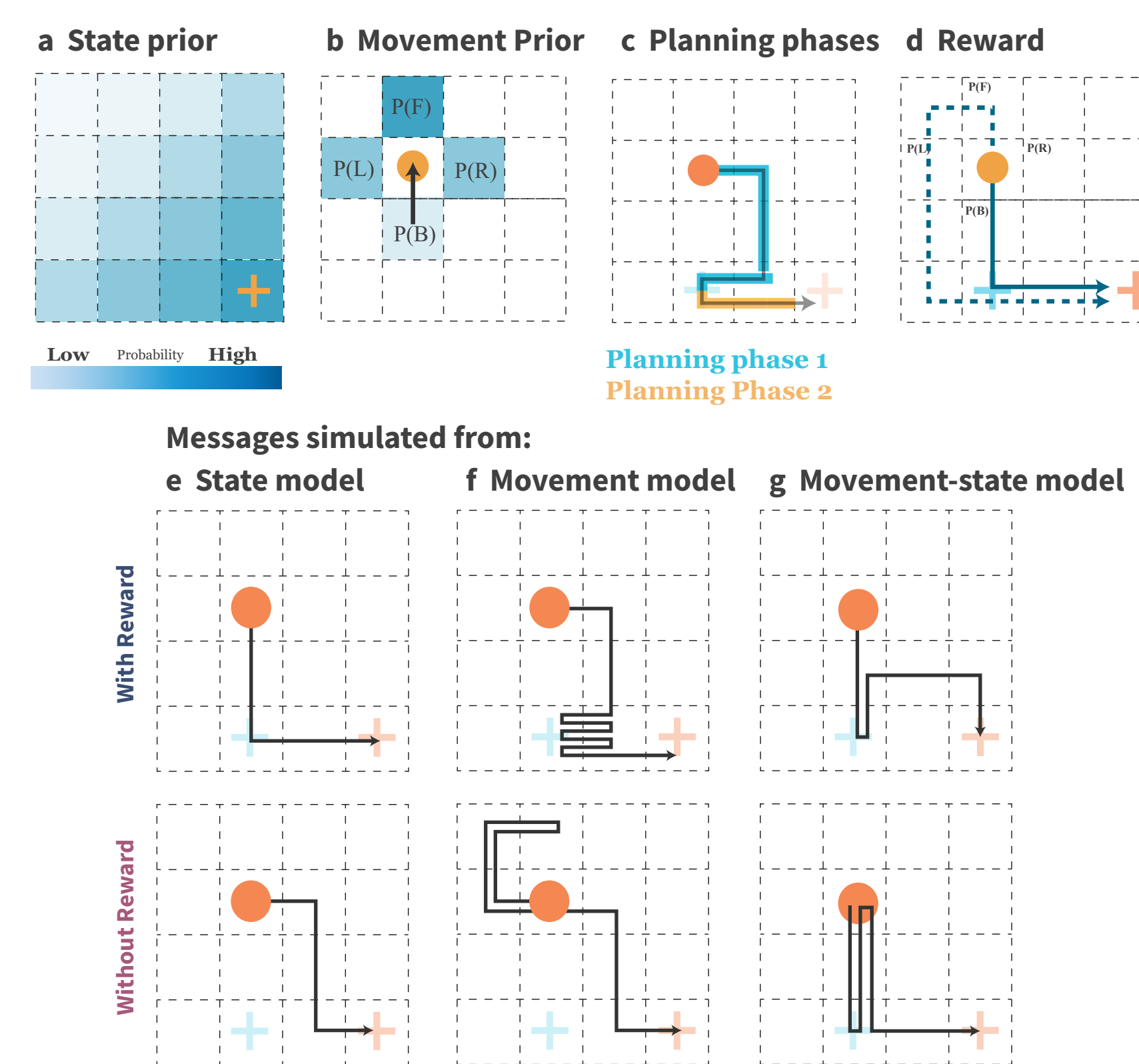
- Background** - Human language-based communication involves both spoken words and prosody to direct the recipient to the important parts of the message [1].
- Research question** - How do humans communicate in novel environments without a common language?
- Proposed mechanism** - Here we propose that **for effective communication surprising events can be used intentionally to signify the salient part of the message by deviating from established expectations.**

### Approach:

- As a testbed for non-language-based communication, we utilized Tacit Communication Game (TCG) and developed a novel computational model to implement the suggested mechanism.
- To assess the performance of the Surprise model, we compared it to the Belief-based Model using data collected from 31 pairs of participants who played the TCG.
- We investigated Pupil dilation and EEG data to quantify the evidence for the Surprise model
- Lastly, we conducted a separate experiment to further validate the effectiveness of different computational models by simulating two senders based on the Surprise model and the Belief-based model, respectively.

## Computational models - Surprise and Belief-based models

### Surprise model: Message Creation

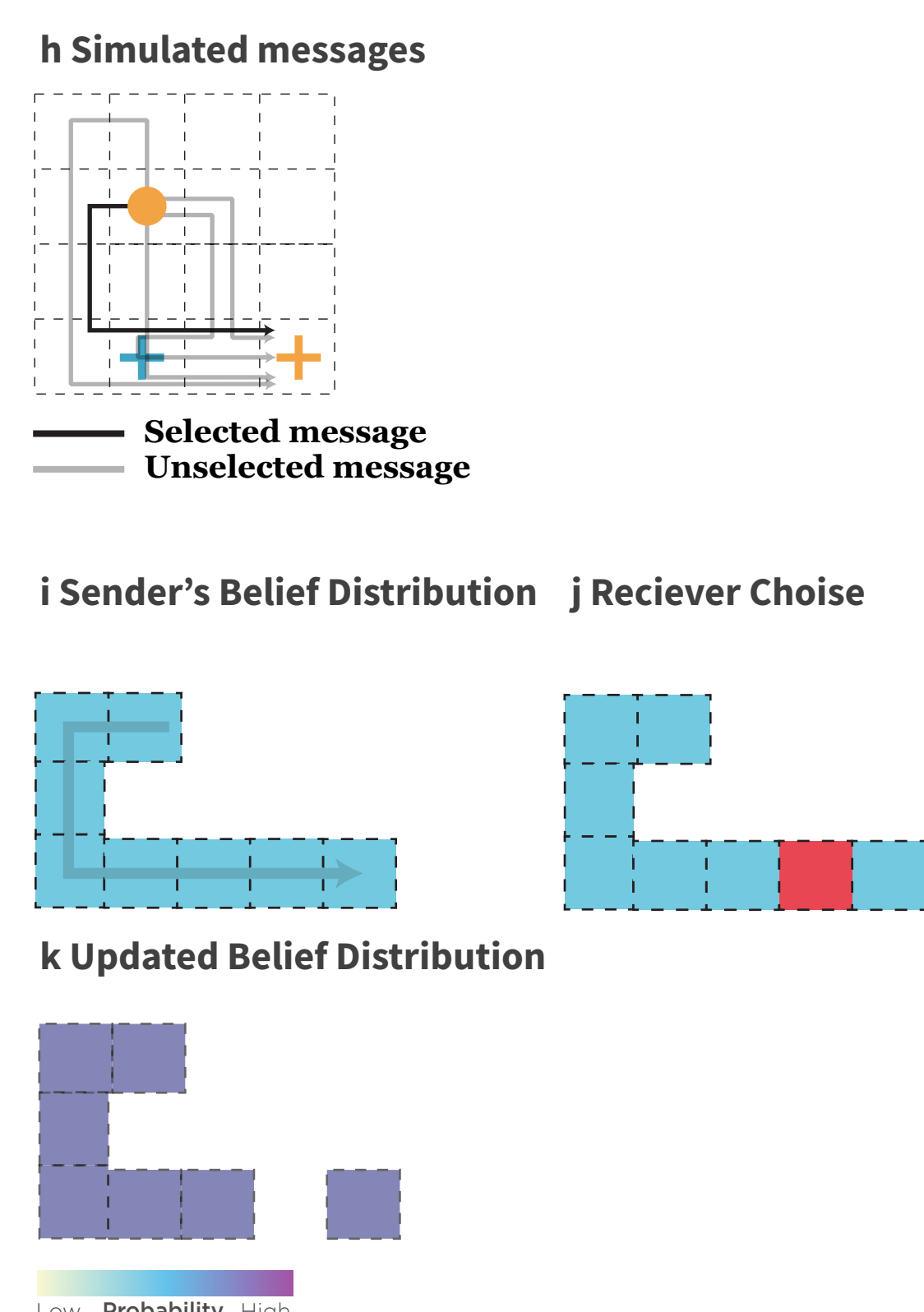


The **Surprise model** employs Action priors and State priors to construct messages, maximizing surprise at the Receiver's goal state.

- Action priors**  $p(f) > p(l) = p(r) > p(b)$
- State Priors** If  $s$  is one step further away from Sender's goal than  $s'$ , then  $p(s) < p(s')$   $p(s) = 1/d \times p(s')$ , with  $d \geq 1$
- Combined state-action priors:**  

$$p(a) = \frac{p(m) \times p(s' | s, m)}{\sum_{m=1}^4 p(m) \times p(s' | s, m)}$$
- Information-theoretic surprise:**  $h(a) = -\log(p(a))$
- Expected value :**  $ev_{a_i | s_i} = -\log(p(a_i) \times e^{lr(s)})$

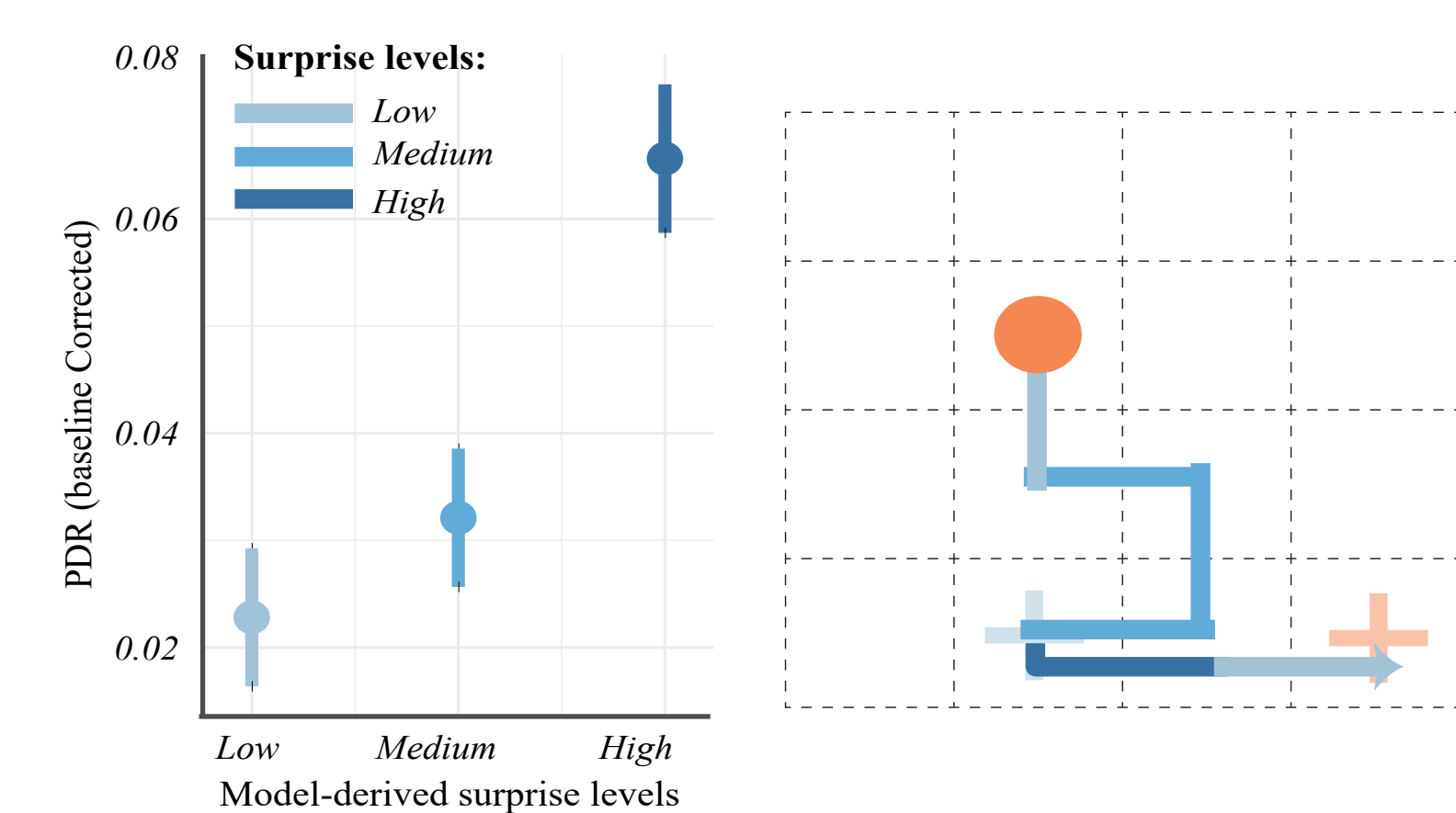
### Belief-Based Model: Message Selection



The **Belief-based model** stores all possible goal-location and message sets (L, M) in memory (Fig.h).

- In each trial:
- The sender observes her and the receiver's goal locations ( $l_s, l_r$ ) and sends a message ( $m \in M$ ) (Fig.h solid line) randomly.
- The receiver observes the message and selects a location ( $l_{EL}$ ) as the goal (Fig. j).
- The sender updates message-specific beliefs based on the receiver's goal success and ToM level[2](Fig.k)

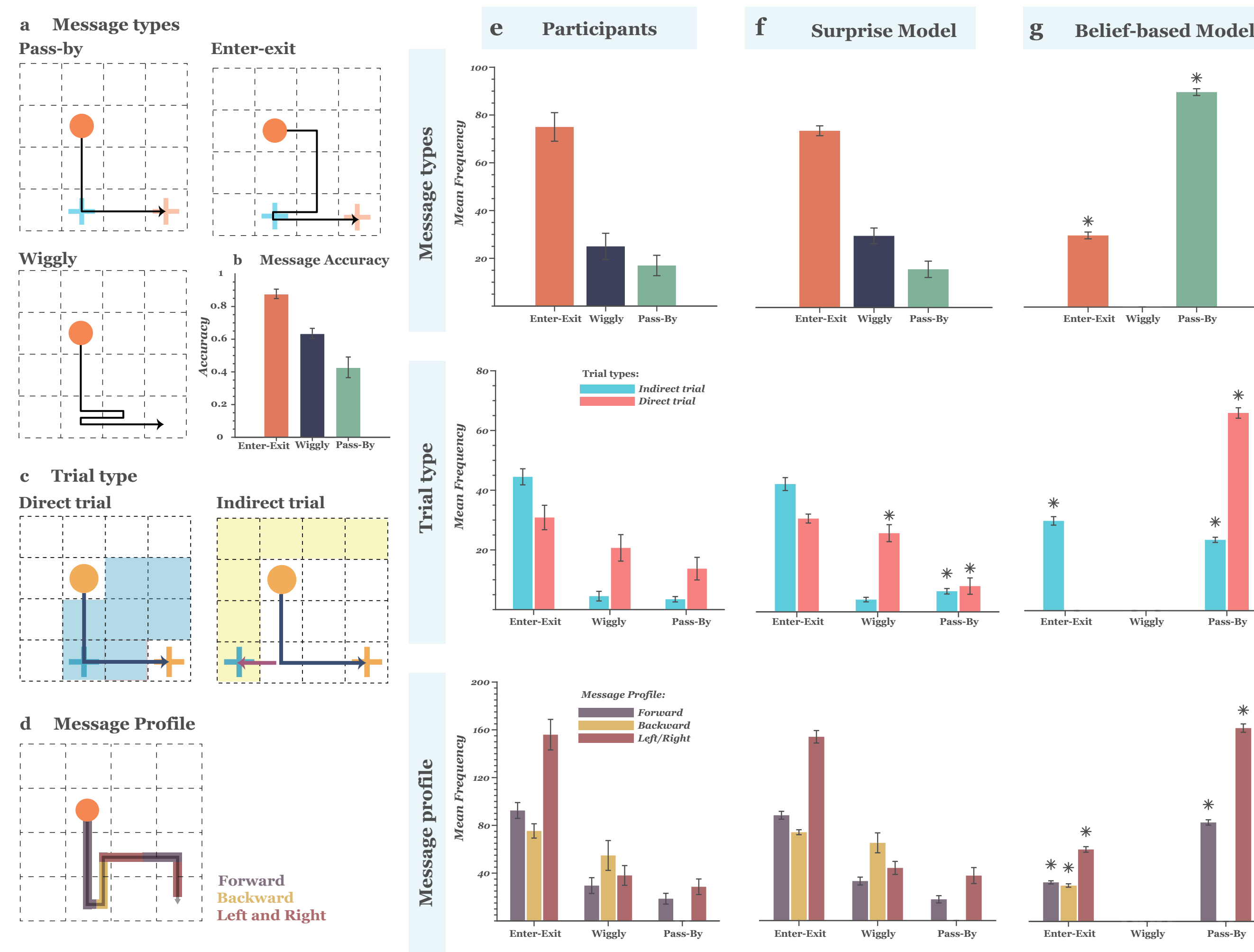
## Model-based analysis of PDR data



Based on the role of the Locus coeruleus in detecting surprising changes in the environmental dynamics [4] and its effect on the pupillary dilation responses [5] we expect that the model's step-by-step surprise will be correlated with the step-by-step PDRs.

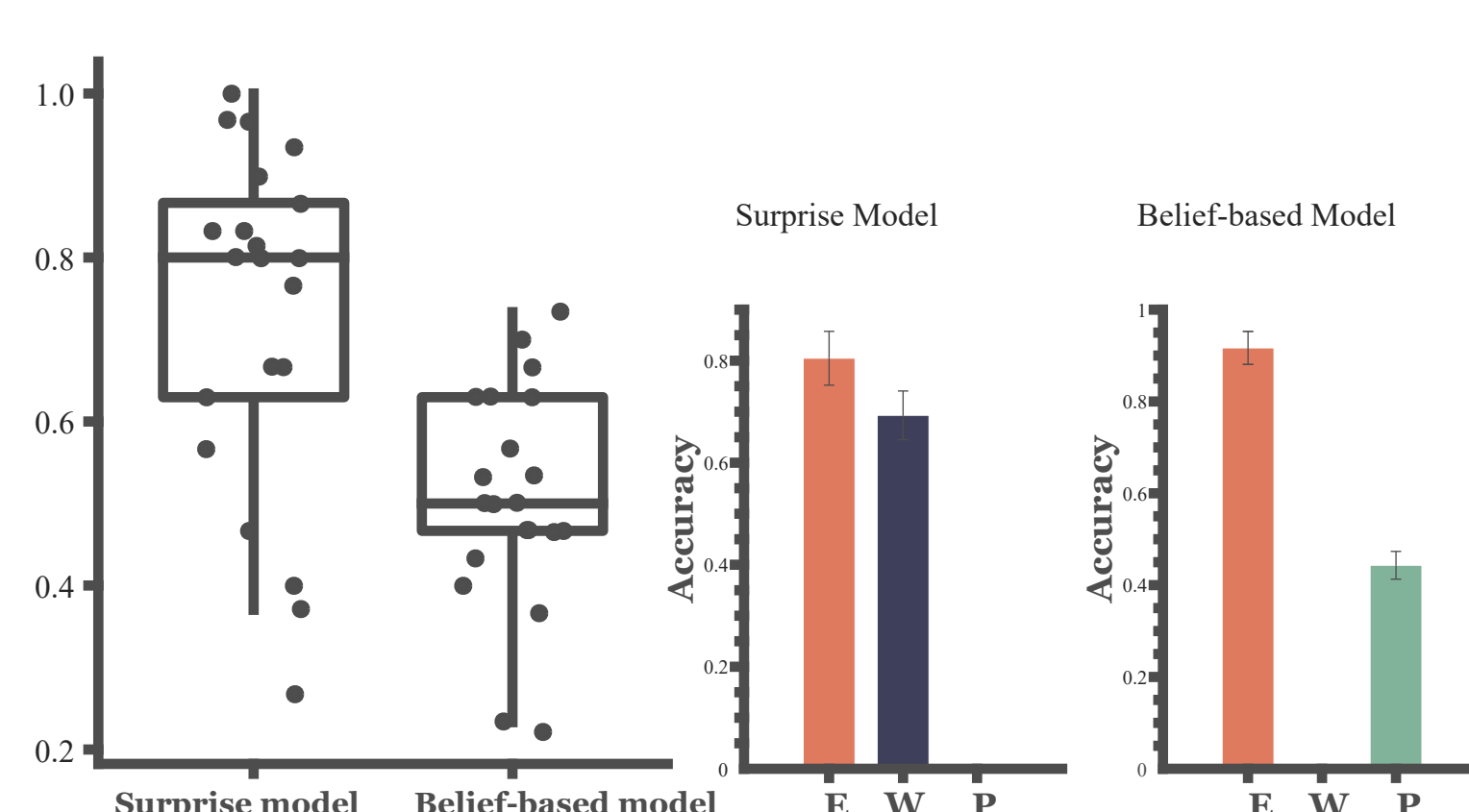
The data showed correlation between model-derived surprising values and pupil dilation ( $p < .001$ ), confirming that uncertainty in the environment can indeed affect the pupil size.

## Model-free analysis of behavioural data and model evidence

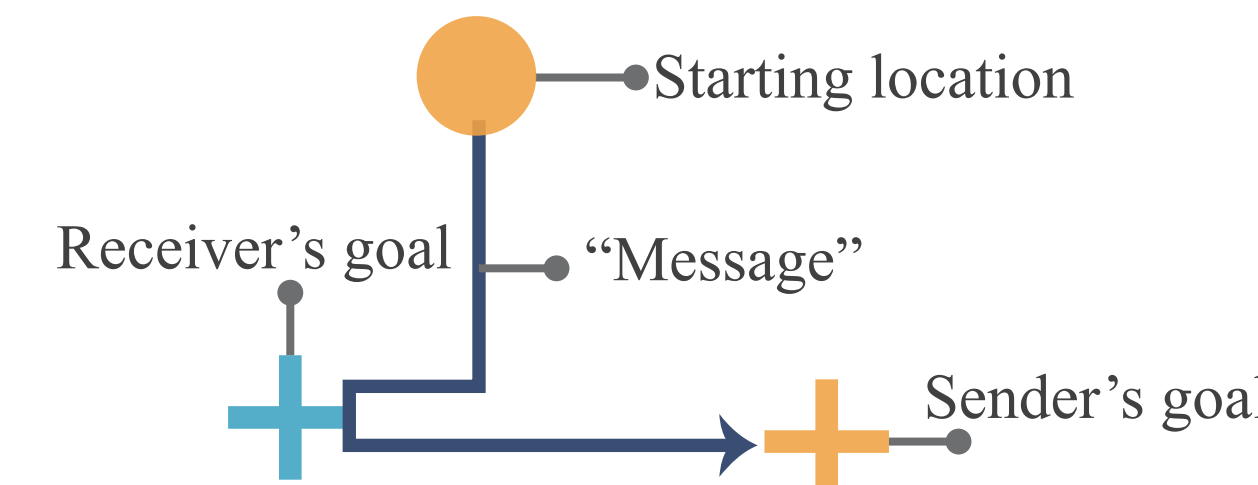


We evaluated two computational accounts using participant-generated and model-simulated messages, focusing on three indices: *Message Type Frequencies*, *Message Profile Frequencies*, and *Message Frequencies across trial contexts*. Comparing human-generated indices to the Surprise model, Bayes factors ( $BF_{01} > 1$ ) strongly suggest similarity. However, compared to the Belief-based model, all Bayes factors ( $BF_{01} < 1^*$ ) indicate differences.

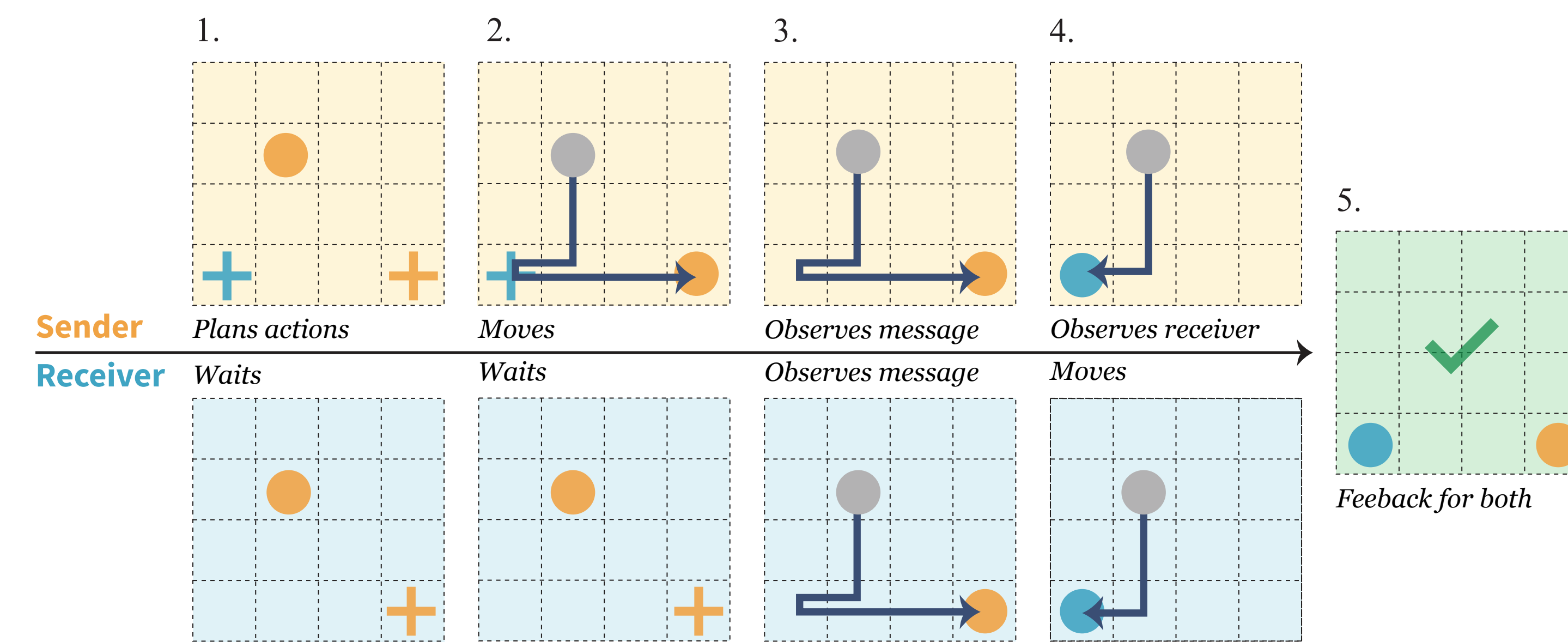
## Effectiveness of computational models with human senders



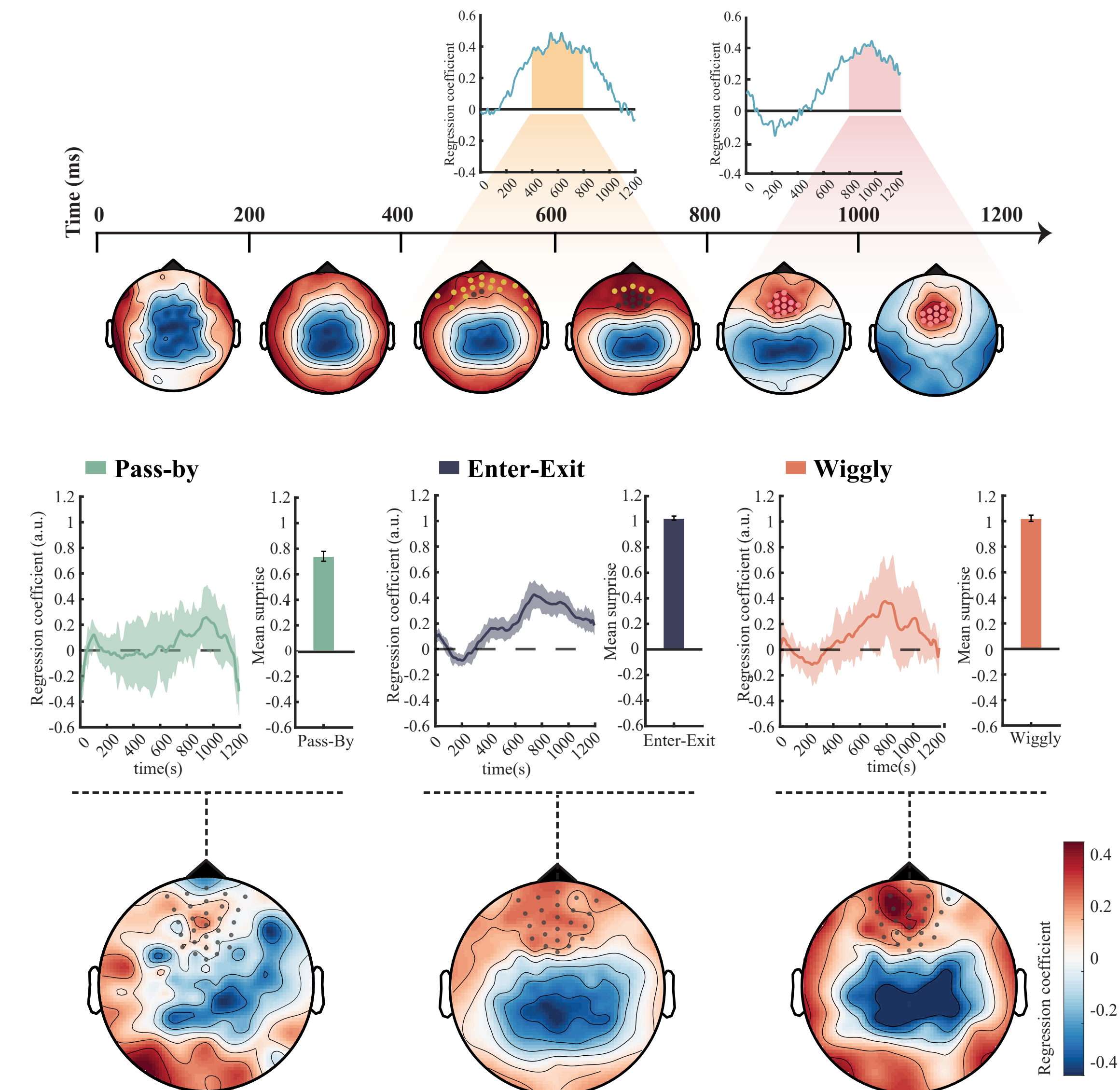
The **Tacit Communication Game** is played on a square game board displaying the goal positions of both players to the Sender. The Sender's objective is to create a trajectory (the "message") from her starting position to her own goal state, effectively conveying the Receiver where his goal location is. The Receiver, in turn, moves his token to the position he believes his goal state to be.



## Experimental task: Tacit Communication Game



## Model-based analysis of EEG data



To study surprise's impact on EEG signals, we employed a model-based regression approach [3].

We identified two clusters of electrodes and time intervals:

- The First cluster showed positive responses in frontal electrodes (400-800 ms),
- Second cluster occurred in frontal-central electrodes (800-1200ms).

## Conclusions

- SM exhibit a notable alignment with human sender behaviors, but it also substantiated its influence through both physiological and neural markers.
  - PDR results indicate that Senders, when designing intentional surprises, significantly impact the physiological states of Receivers.
  - EEG results showed two cluster sensitivity to surprise, the first cluster located above the anterior prefrontal cortex, can be associated with high level action planning and second, central-frontal cluster located above ACC can be associated with detection of prediction error.
  - Letting the Human senders playing the game with the models showed that creating surprising events can be helpful in communication.
- The results suggest that in the absence of common language, individuals intentionally use surprise to convey important information. This differs from the traditional understanding of prediction errors in learning and decision-making [6].

### Acknowledgments

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[1] Dahan, D. Prosody and language comprehension. Wiley Interdiscip. Rev. Cogn. Sci. 6, 441–452 (2015).

[2] de Weerd, H., Verbrugge, R. & Verheij, B. Higher-order theory of mind in the Tacit Communication Game. Biologically Inspired Cognitive Architectures 11, 10–21 (2015).

[3] Fischer, A. G., Nigbur, R., Klein, T. A., Danielmeier, C. & Ullsperger, M. Cortical beta power reflects decision dynamics and uncovers multiple facets of post-error adaptation.

[4] Preusschoff, K., 't Hart, B. M. & Einhäuser, W. Pupil Dilation Signals Surprise: Evidence for Noradrenaline's Role in Decision Making. Front. Neurosci.

[5] Sara, S.J. & Bouret, S. (2012). Orienting and Reorienting: the Locus Coeruleus mediates cognition through arousal. Neuron, 76, 130-141.

[6] Sutton, R. S. & Barto, A. G. Reinforcement Learning, second edition: An Introduction. (MIT Press, 2018).